A Comparison of NOAA RUC Analysis Surface Winds and ADAS-Enhanced RUC Analysis Winds with Surface Observations

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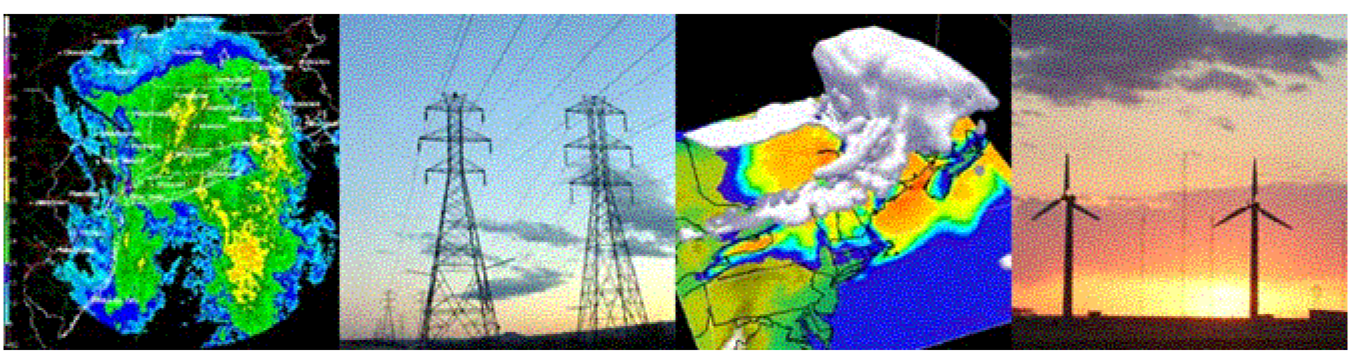

A Comparison of NOAA RUC Analysis Surface Winds and ADAS-Enhanced RUC Analysis Winds with Surface Observations

Dr. Dennis A. Moon

Abstract:
One year of wind field data from hourly NOAA Rapid Update Cycle (RUC) analyses is compared with surface observations over western North and South Dakota and eastern Montana. A similar analysis is performed on a set of wind fields derived from the RUC data, enhanced by assimilation of surface observations using the University of Oklahoma ARPS Data Assimilation System (ADAS) system. Strong correlations between the gridded and observational data are observed, with R^2 values exceeding 0.9 in most cases. Better correlation is seen for stronger wind situations. Errors in the RUC speed and directional data are reduced by approximately 40% by application of the ADAS system.

Introduction:
The CALMET/CALPUFF modeling system has been promulgated by the US EPA for regulatory permitting usage. CALMET is a diagnostic wind-field model used to generate three-dimensional meteorological fields as inputs to the CALPUFF dispersion modeling system. While CALMET is capable of generating these fields directly from a set of surface and upper air observations, such fields lack dynamic consistency as implied by the equations of motion. While CALMET does adjust the wind fields to conserve mass, conservation of momentum, thermodynamic energy, and water substance are not observed. Prognostic models take these quantities into account including non-linear and time derivative terms. As a consequence, the EPA encourages the use of meteorological fields from a prognostic model as first guess fields, by allowing the use of three years of meteorological data when using prognostic model fields as opposed to five years required when using traditional meteorological data. (US EPA 40 CFR Part 51, Appendix W) CALMET is then used to blend the observational data into background fields from the prognostic model.

The Mesoscale Model version 5 (MM5) modeling system from the National Center for Atmospheric Research (NCAR) and Pennsylvania State University is the most widely used mesoscale modeling system, having been deployed in a wide range of research and operational settings , see (http://www.mmm.ucar.edu/mm5/mm5-home.html). Meteorological fields from MM5 are frequently used as a source of first-guess fields for CALMET, and indeed the CALMET system includes software tools for the conversion of MM5 generated datasets into a CALMET-specific input text format. Use of the MM5 model allows for custom grid resolution and specification of physical parameterizations as required to represent the relevant flow features for a given location. In addition, the model includes a Four Dimensional Data Assimilation (FDDA) capability, which can be used to “nudge” the model towards the actual solution when applied to past cases for which observed data is available.

Another source of prognostic modeling data that has not been as widely considered within the air quality modeling community are the real-time modeling systems from the National Center for Environmental Predictions (NCEP). NCEP is charged with the task of development and operation of the suite of models used by the National Weather Service forecast operations. An integral step in the process of generating a model-based forecast is the preparation of the initial (or analysis) fields. This entails preparation of a three-dimensional, gridded analysis of the state of the atmosphere with as much accuracy as possible. This process involves using an assimilation system to blend the most recent observational data with first-guess fields from previous runs.

Of particular interest is the Rapid Update Cycle (RUC) system used to provide frequently updated short-term forecasts. The RUC cycle is unique among the NCEP forecast systems in that analyses are produced every hour, versus every six hours for the other models used for longer term forecasting, such as in the Eta and GFS modeling systems. The RUC cycle uses a process known as continuous assimilation, in which short, one hour forecast segments are interspersed with applications of the data assimilation process. This means that each hour, the one-hour forecast fields are corrected, based on the real-time data collected by The National Oceanographic and Atmospheric Administration (NOAA). These corrected fields serve as the starting point for the CALMET analysis described here. The one-hour analysis time step (not to be confused with the much smaller internal time step used within the RUC forecast model) is important in that the short duration for the forecast phase limits the magnitude of forecast errors that are an inevitable consequence of running any prognostic model. The model is never allowed to stray too far from the actual state of the atmosphere, within limits determined by observational sampling frequency, density, and accuracy. Frontal positions, for instance, can be reasonably well adjusted for in the assimilation process providing that the model frontal positions are close to those supported by the observations.

The one-hour analysis interval of the RUC system is also important for air quality modeling, in that CALMET requires its meteorological fields on a one-hour time step. Continuous assimilation cycles are complex and computationally expensive to run; however one can take advantage of the NOAA RUC cycle by using archives of the hourly analyses. In addition, NOAA, both NCEP and the Forecast System Laboratory (FSL), the developers of RUC, have access to a wealth of real-time observational data resources well beyond that available to private entities. As a result, their analyses include a more complete set of observations than could be assembled in an attempt to run a custom continuous assimilation cycle. Table 1 shows the data resources utilized in the RUC process.

Table 1

Data Type	**Number**	**Frequency**	**# obs in Study Area**
Rawinsonde (inc. special obs)	80	/ 12h	2 (see figure 1)
NOAA 405 MHz profilers	31	/ 1h	0 (see figure 2)
VAD winds (WSR-88D radars)	110-130 / 1h		3 soundings (see figure 3 for more information)
Aircraft (ACARS) (V, temp)	1400-4500 / 1h		Some flight level winds/no vertical profiles
Surface/METAR - land (V, p_{sfc}, T, T_d)	1500-1700 / 1h		22 (see figure 4)
Buoy	100-150	/ 1h	NA
GOES precipitable water	1500-3000 / 1h		complete coverage
GOES cloud drift winds	1000-2500 / 1h		complete coverage
GOES cloud-top pressure	~10 km res / 1h		complete coverage
SSM/I precipitable water	1000-4000 / 6h		complete coverage
Ship reports	10s	/ 3h	NA
Reconnaissance dropwinsonde	a few	/ variable	NA

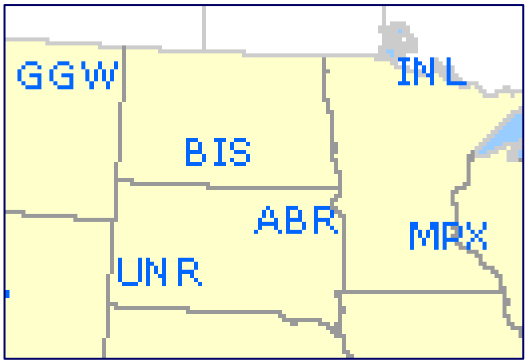

Figure 1. Location of radiosonde locations surrounding North Dakota

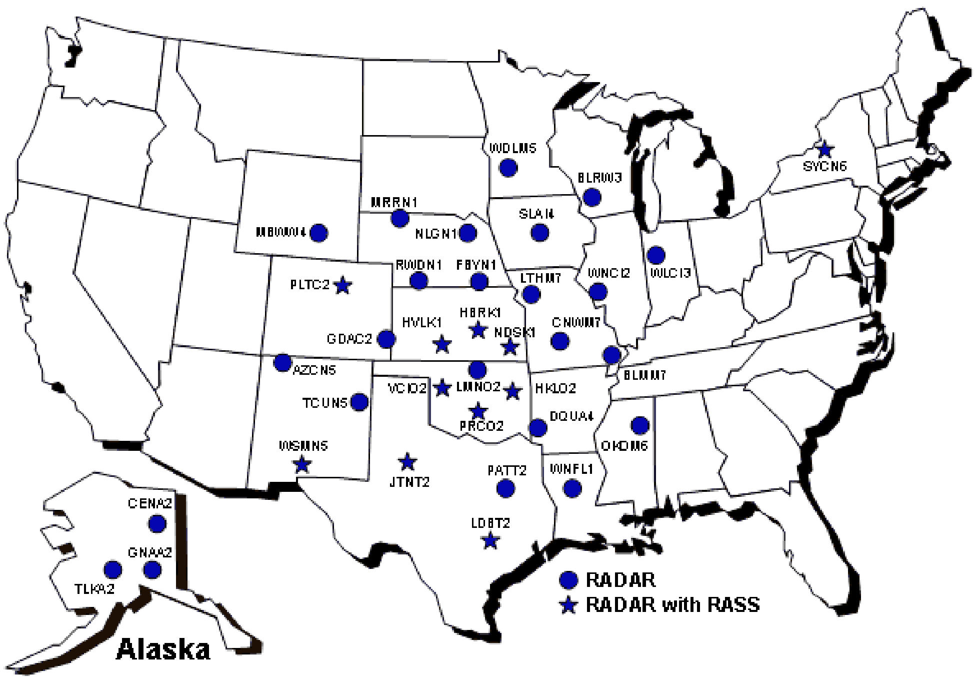

Figure 2. Locations of profiler and RASS stations

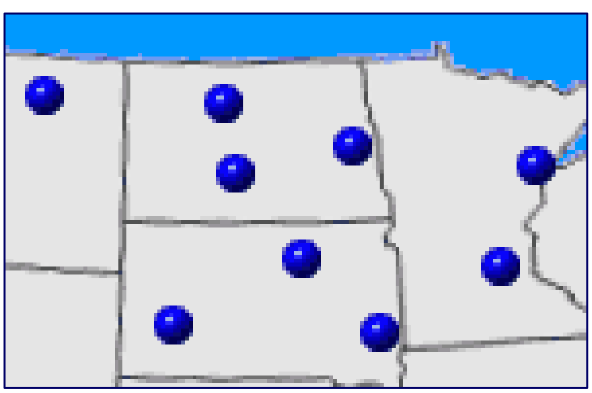

Figure 3. Locations of NWS-88D radars (normally 5-15 VAD wind levels available at each site, depending on atmospheric conditions).

The greatest value in the use of these analysis datasets as opposed to going back and re-simulating a time period using a mesoscale model lies in the application of the continuous assimilation process. Even when run in retrospective mode, model simulated fields will exhibit significant differences from observations. We often refer to this as "forecast" error and it is the result of imperfections in the finite representation of the continuous equations of motion, simplifying assumptions in the treatment of complex physical processes such as turbulence, radiation and cloud microphysics, errors in the representation of the soil and vegetative properties, and errors in the initial and boundary conditions supplied to the model which reflect the relatively low sampling density of the observational network. The net result is that while the flow patterns and resultant weather features are generally well simulated when considered from a pattern matching point of view, point time-series extracted from model simulations exhibit significant error, even when taken from what would be considered an excellent simulation. When simulating a long time-series the model must be periodically re-initialized from the archived data in order to eliminate model drift. Typically this might be done by restarting each day of the simulation, resulting effectively to the generation of a series of 24-hour forecasts.

Harrison (2003) discusses a comparison between 12-hour MM5 model forecasts and surface and upper air observations in the Pacific Northwest region over an 18-month period. The MM5 employed a grid resolution of 4 km. Model solutions were interpolated to the observation locations. Considering the surface (10m) wind results, he found the Root Mean Square (RMS) speed error to be 2.46 m/s, as compared to a mean wind speed of 2.55 m/s. The model surface direction showed a bias of –15.65 degrees, indicating a tendency for the model wind directions to be rotated clockwise or veered from the observations. The RMS direction error was a discouraging 73.65 degrees. He also calculated the coefficient of determination, R^2, for the matched model and observed wind vectors. The interpretation of this quantity is that a value of 1.0 indicates a perfect match, a value of 0.0 indicates a correlation between the two data sets no greater than that achieved by substituting the mean quantities as predictions (using climatology), and negative values indicate less correlation than the climatology. He reports a negative value of R^2 value at negative 1.25.

It should be noted that the Pacific Northwest weather patterns are strongly influenced by coastal and topographic effects, making it a very challenging area to model. However these values are not out of line with other sources. When comparing the NCEP Eta model forecasts against 50m winds observed at a Midwestern wind turbine facility, WindLogics observed a <u>residual</u> mean absolute error (MAE) of 1.84 m/s after adjusting the model forecasts to remove the bias by applying a linear fit between the two sets of data. Brundage et al (2001) report on a comparison of 12-hour RUC model forecasts on a 40km grid against tower data. For a 10m AGL site near Golden Colorado, they report an RMS error for wind speed of 2.96 m/s. Comparing against 30m AGL tower measurements they report an RMS error of 2.49 m/s for a site in Southwest Minnesota.

The use of FDDA to nudge the simulation towards observed values can be of help in obtaining MM5 solutions that more closely match the observations, although in practice the use of FDDA can be problematic. Point nudging is a technique whereby the model experiences additional forcing terms at grid cells in the vicinity of an observational point which are proportional to the difference between the grid point value and the observed value. In this way the model solutions are "encouraged" to agree with the point values. This works well when in cases where the model solutions are inherently "close" to the observations, hence the apt choice of a name for the technique, nudging. In cases where the model solution diverges significantly from the observations the process of nudging can result in some very un-physical looking flow structures in the vicinity of the observations. This is particularly true in cases where the wind directions disagree. The problem is that the model winds at any point are the result of a complex set of interactions involving the mass and momentum fields over a large area. The process of nudging the model grid points near the observations cannot affect the large scale field from which the model winds result, in any meaningful way.

Model first-guess fields derived from RUC archives have the advantage of being analyses rather than forecasts. That is, they reflect the level of error in the initial conditions used for the RUC model rather than the forecast errors. Therefore it would be expected that in many cases they should be suitable for use as high-quality first-guess fields for the CALMET modeling process. We present here a comparison of the RUC analysis wind fields, from a 40 km grid, with metar 10m AGL observations over a CALMET domain in the Northern Plains. The intent is to quantify the surface wind error characteristics of this data source and this region.

As a second step, we compare the observations against the RUC data enhanced by using the University of Oklahoma ADAS assimilation system to re-assimilate the observations into the RUC data on a finer 10km grid. The ADAS system, see Brewster (1996) and the CAPS web page (http://www.caps.ou.edu/ARPS/ADAS432.doc.htm), is a highly regarded mesoscale assimilation system with which we have considerable experience, using it to provide initial conditions to ARPS and MM5 mesoscale model runs. The primary goals here were to enable incorporation of observed data that arrived too late to be included in the real-time RUC analysis process, and by going to a finer grid, to allow the gridded system to more accurately reflect the variations between observations. It should be noted that the objective here was to enhance the data for CALMET processing, rather than to compare the merits of the RUC and ADAS assimilation systems, so the positive effect of the higher grid resolution is included in the results.

A couple of limitations inherent in the RUC data files should be mentioned. First, the RUC system is a real-time system operating on a tight time schedule. For this reason, late arriving observations may be missed in the RUC assimilation process. This is one of the key reasons for re-assimilating the observational data after the fact using ADAS. Second, the grid spacing available in the RUC archives is 40 km prior to 2003, and 20 km from there forward. For many parts of the country that is sufficient resolution to accurately represent the dynamical systems responsible for the wind field structure. The 20 km data in particular appears to do a reasonable job of resolving mesoscale features such as sea breezes, although undoubtedly the detailed sea-breeze frontal structures are smoothed out compared to reality. In cases where the mesoscale forcing is strong, and the horizontal scale of mesoscale organization (primarily due to terrain effects) is small relative to the RUC grid size the RUC data may not resolve the relevant flow features. In such cases it may make sense to use a mesoscale model run to generate the meteorological fields. The determining factor is whether the improvements in resolving the mesoscale flow patterns outweigh the additional forecast error incurred by the model. An example might be thermally driven flows between the California Central Valley region and the Mohave Desert where the details of the flow are determined by small-scale terrain features such as passes through the mountains, which serve as flow channels. Interaction with the terrain would also serve to excite gravity wave modes in the atmosphere. In such a regime, the 40km or 20km RUC data could not be expected to resolve the fine scale features and a high resolution MM5 solution would be more appropriate.

Procedure:
The study domain is shown in Figure 4, with the location of the comparison points highlighted in red, and the 40 km RUC grid shown in green. Also shown are surface metar stations within the study area. All of the stations shown are used by NCEP in the RUC process. The stations marked with dots show those with archived data available in the WindLogics archives for the process of re-introduction using ADAS and for the validation process.

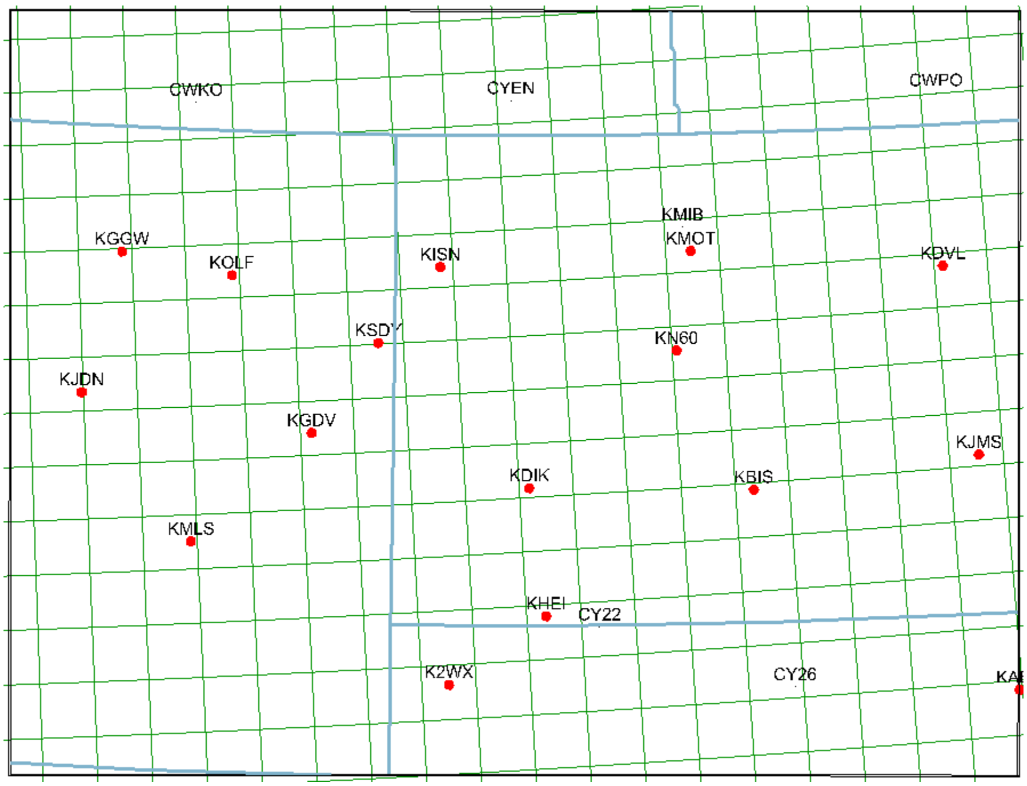

Figure 4. Computational Domain and 40 km RUC grid. Dots indicate metar stations used for validation

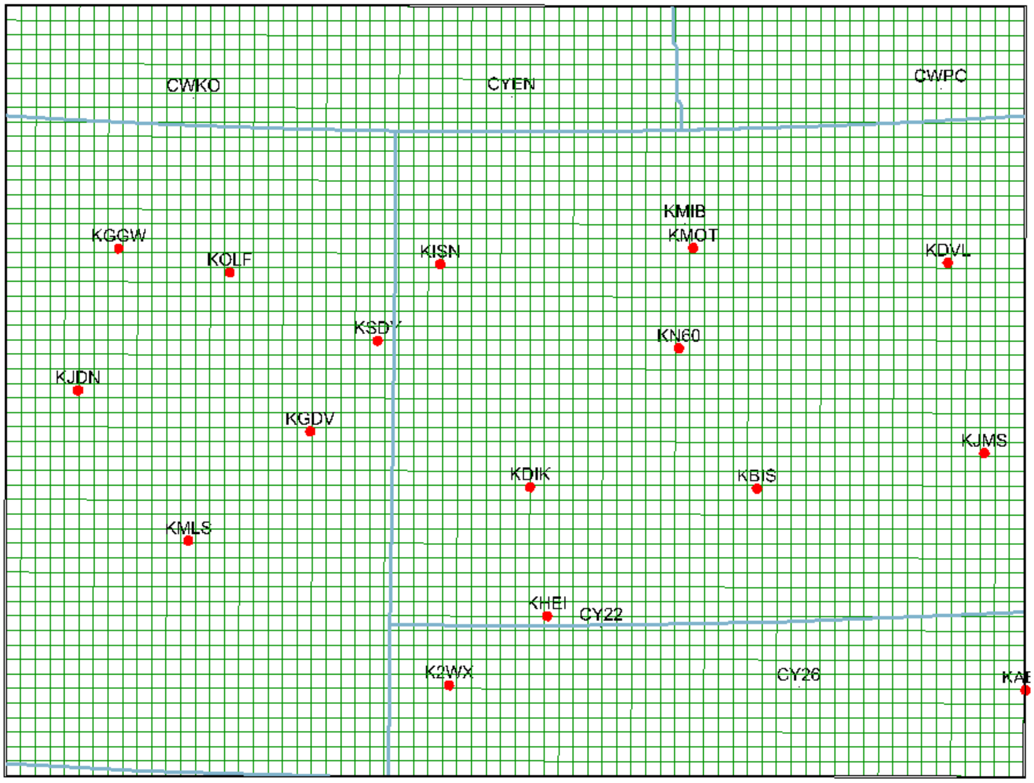

Figure 5. Study Domain with the 10 km grid used in the ADAS processing. Dots indicate metar stations used for validation.

The comparison period is for calendar year 2002 at 16 observing stations, as indicated by the dots on figures 4 and 5, representing a total of about 117,000 matched observation/model pairs. The analysis procedure was to first calculate the Cartesian X and Y coordinates of the grid points and observation locations within the map projection system of the grid, in this case a Lambert grid. Within this system the grid is orthogonal and aligned with the X and Y coordinate, allowing for simple bilinear interpolation of the gridded 10m AGL wind components to the observations locations. In both cases, the 40 km RUC data and the 10 km ADAS data, the four grid points surrounding the observation location were used in the interpolation process. Observations of calm were included in the speed calculations but excluded from the directional analysis. The surface observations, RUC data, and RUC/ADAS data were all accessed from netCDF binary random access files.

Statistical measures relating to the speed and directional error were then derived from the matched data pairs. These included:

- Mean absolute Error:

$$\mathrm{MAE} = \overline{\left|(Y_m - Y_o)\right|}$$

Where Y is speed or direction. Note that directional errors were always normalized to be less than 180 degrees. The "o" and "m" subscripts indicate that the values are for observation or model data respectively.

- $\text{BIAS} = \overline{(Y_m - Y_o)}$

- The Vector errors were defined as the magnitude of the vector difference between the model and observed winds.

  $\text{Vector MAE} = \overline{\left|(\vec{V}_m - \vec{V}_o)\right|}$

- Coefficient of determination, R^2, defined as:

$$R^2 = 1 - \frac{\sum\left[(U_o - U_m)^2 + (V_o - V_m)^2\right]}{\sum\left[\left(U_o - \overline{U_o}\right)^2 + \left(V_o - \overline{V_o}\right)^2\right]}$$

Where:
- U_0 is the observed X-component of the wind
- V_0 is the observed Y-component of the wind
- U_m is the model predicted X-component of the wind
- V_m is the model predicted Y-component of the wind

Results:
A summary of the speed error statistics is shown in Table 2. The numbers in the "RUC" column reflect the 40 km RUC errors and the "RUC/ADAS" column shows results for the enhanced RUC data on the 10 km grid. In addition to the overall statistics, results are shown for "fast" and "slow" cases, with slow being observations less than or equal to 5 kt (2.57m/s). Speeds below 5 kt were considered indicative of typical light wind, frequently nocturnal, cases that present a challenge to models.

Table 2:

	Speed MAE		**Speed Bias**		**Vector MAE**		**R^2**	
	RUC	**RUC / ADAS**	**RUC**	**RUC / ADAS**	**RUC**	**RUC / ADAS**	**RUC**	**RUC / ADAS**
< 5 kt	0.563	0.341	0.266	0.162	0.790	0.478	0.613	0.814
> 5 kt	0.608	0.335	-0.283	-0.016	0.953	0.587	0.955	0.982
All	0.597	0.336	-0.145	0.029	0.912	0.559	0.932	0.972

Speed data in m/s

The RUC speed analysis results are encouraging. Referring to the overall results, we see that the mean absolute error is less than 0.6 m/s as compared to a typical forecast error of 2 m/s or more. While not surprising that a set of initial conditions files should exhibit superior error characteristics compared to a forecast, it is important to validate the concept for air quality usage. The speed bias is –0.145 m/s indicating that the RUC analysis winds were on average very slightly slower than the observed winds. The vector results were also encouraging. While the other studies don't specifically cite this quantity, the vector errors are typically around 50% larger than scalar speed errors. The RUC vector MAE is less than 1 m/s as compared to forecast errors typically in the 3 m/s range. The coefficient of determination indicates strong correlation between the RUC and surface observations datasets with a 0.93 value. Looking at the results for slow and fast wind separately, we see for the speed MAE, vector MAE, and speed bias that the errors for the fast category are all slightly larger than for the slow winds. The R^2 value shows a fairly significant difference between slow and fast. The fast winds are highly correlated with a value over 0.95, while for the slow wind subset the correlation is reduced to 0.61, a value that still indicates a good correlation. The reason for this can be seen in the definition of R^2. The wind errors are scaled by the magnitude of the deviations from the average value. The lower coefficient of determination for the slow wind cases indicates that while the magnitude of the errors may be slightly lower than for the high wind cases, the relative error compared to normal speed deviations is larger. This is not a surprising result as the actual deviations from normal will naturally be smaller for the low wind case.

The RUC/ADAS analyses show a marked error reduction over the straight RUC data. The error magnitudes are reduced in most cases by 40% or more, with the speed and vector MAE values at 0.34 m/s and 0.56 m/s respectively. The speed bias is negligible at about 0.03 m/s. Not surprisingly the coefficient of the determination shows stronger correlation with the observations. Comparing the slow versus fast samples, we see the same trends as in the RUC results, although in this case the R2 value for the slow wind cases drops to 0.81 as compared to 0.61 for the RUC.

A summary of directional errors is shown in Table 3.

Table 3:

	Direction MAE		Direction Bias	
	RUC	RUC / ADAS	RUC	RUC / ADAS
< 5 kt	16.534	9.872	1.862	2.767
> 5 kt	7.029	4.478	0.186	0.699
All	8.87	5.52	0.510	1.098

Directional data in degrees

The RUC directional MAE for all cases was 8.9 degrees. It is difficult to make a meaningful comparison with the Harrison results given the differences in meteorological regimes, except to say that directional errors were about a factor of 8 lower for the RUC data and this domain. The slow wind cases tended to show more directional error than with fast wind, with just over double the MAE at 16.5 degrees. At 10m AGL the slower wind fields often occur at night, when strong thermal stability can work to decouple the low level winds from the synoptic pattern to varying degrees. As a result, the wind pattern becomes dominated to a much greater extent by local phenomena such as drainage flows, which exhibit low spatial correlation. Nearby stations can frequently be seen with great differences in wind direction. In such cases the assimilation system (RUC or ADAS) is dealing with highly variable fields with weak magnitudes, degrading the directional analysis. An example low wind case is shown in figure 6. As with speeds, the directional biases were very small in all cases.

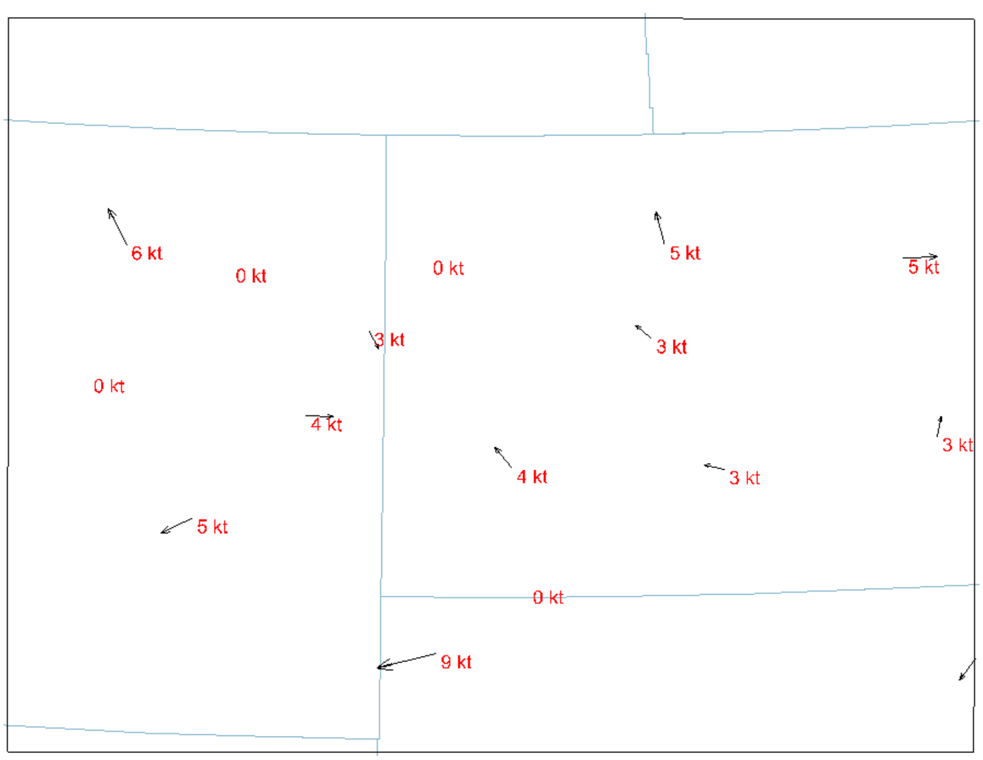

Figure 6. An example of light and variable winds

For directional MAE the RUC/ADAS result showed marked improvement over the RUC errors. The error reduction was again about 40% compared to RUC, for all both speed classes. The RUC/ADAS directional bias was slightly larger then the RUC result but still very small.

Figures 7-9 show more detail into the distribution of the errors, for speed, direction, and vector errors. In general the RUC/ADAS errors are more tightly clustered around the zero point, with larger contributions on the tail portions of the curves from the raw RUC data.

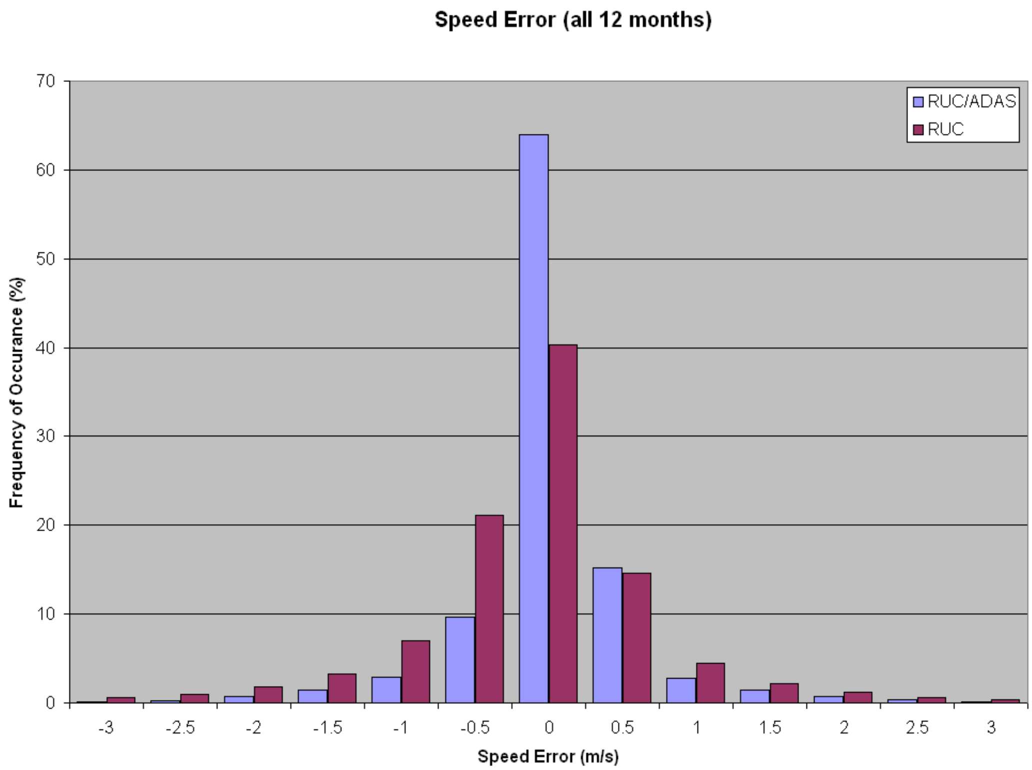

Figure 7. Speed error distribution for RUC and RUC/ADAS

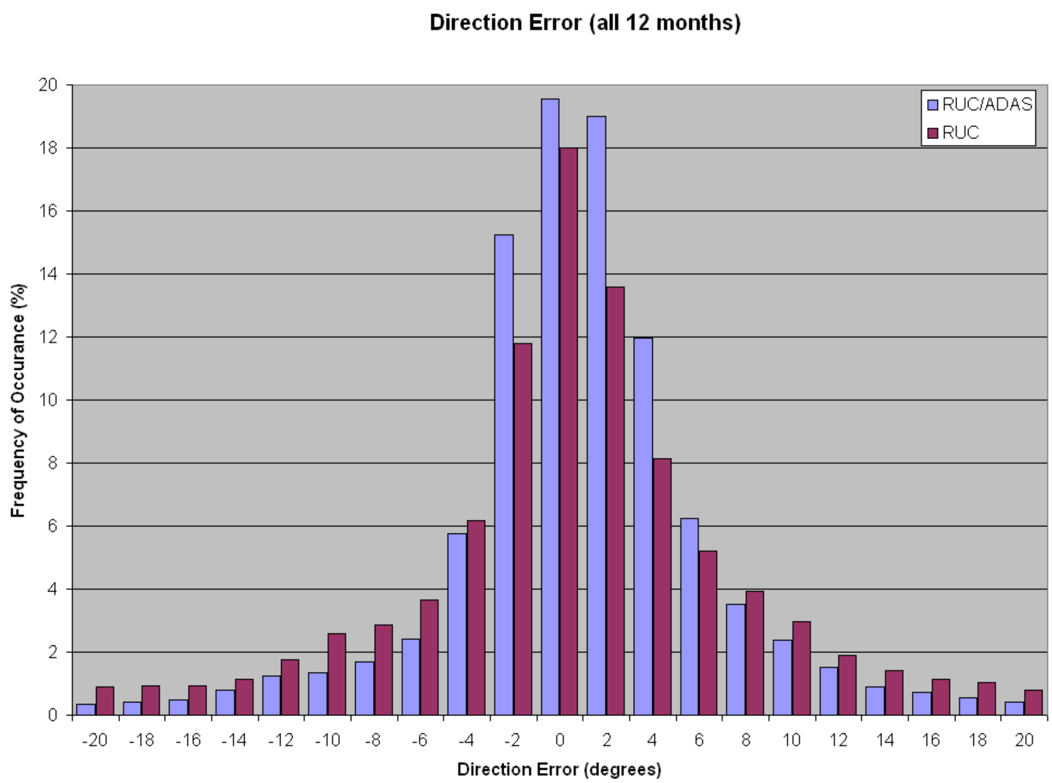

Figure 8. Directional error distribution for RUC and RUC/ADAS

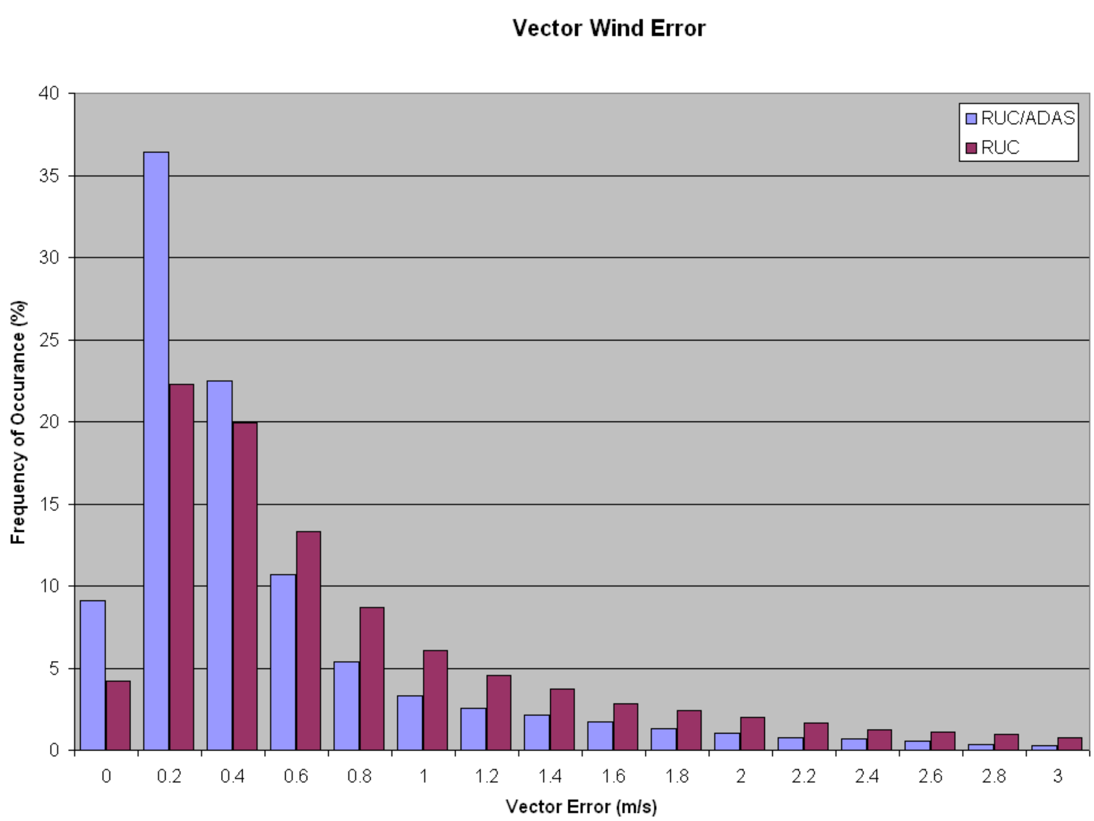

Figure 9. Vector error distribution for RUC and RUC/ADAS

A diurnal analysis was performed to determine if there were significant influences on the error characteristics. Error statistics were accumulated separately for each hour of the day, with results shown in figures 10-14. The only noticeable trend regarding the speed and direction errors was slightly higher errors around the 00Z and 12Z timeframes. We believe that the explanation for this lies in the fact that those are the times when large amount of upper air observations are applied to the assimilation process. Surface observations in the vicinity of an upper air site have relatively less weight in the interpolation process. The RUC data shows a slight negative speed bias for all times, but the effect is most evident in the daytime hours, with a typical bias of ~ -0.23 m/s versus approximately -0.1 m/s during nighttime hours. These small errors are corrected for in the ADAS assimilation process.

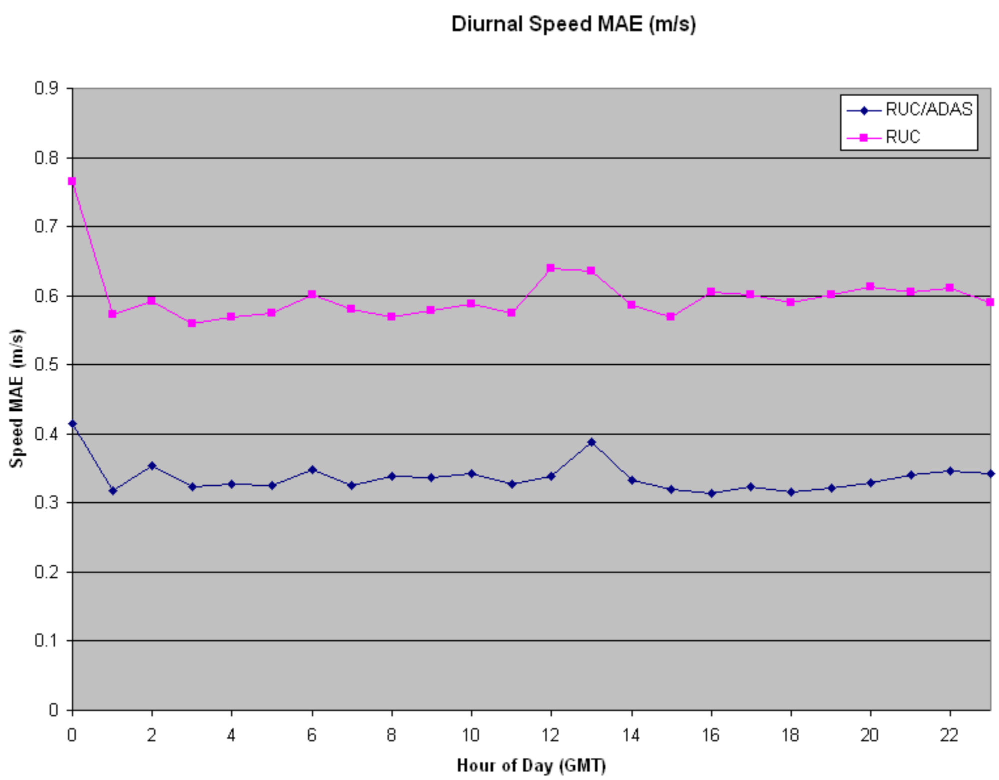

Figure 10. Speed MAE as a function of time of day

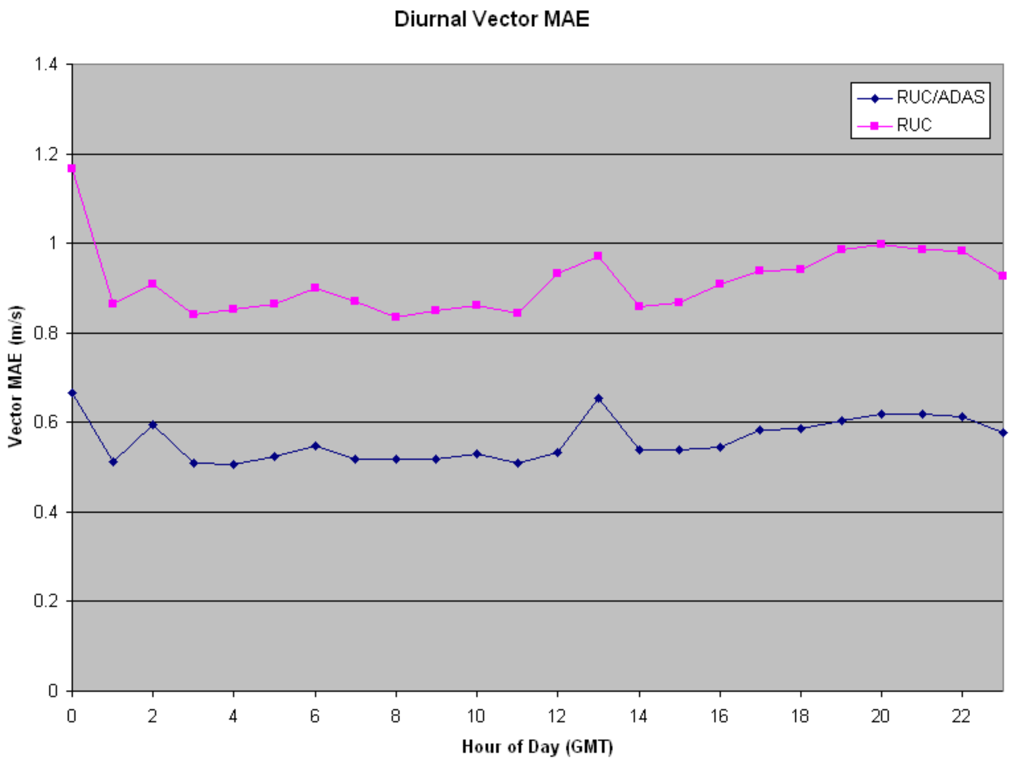

Figure 11. Vector MAE as a function of time of day

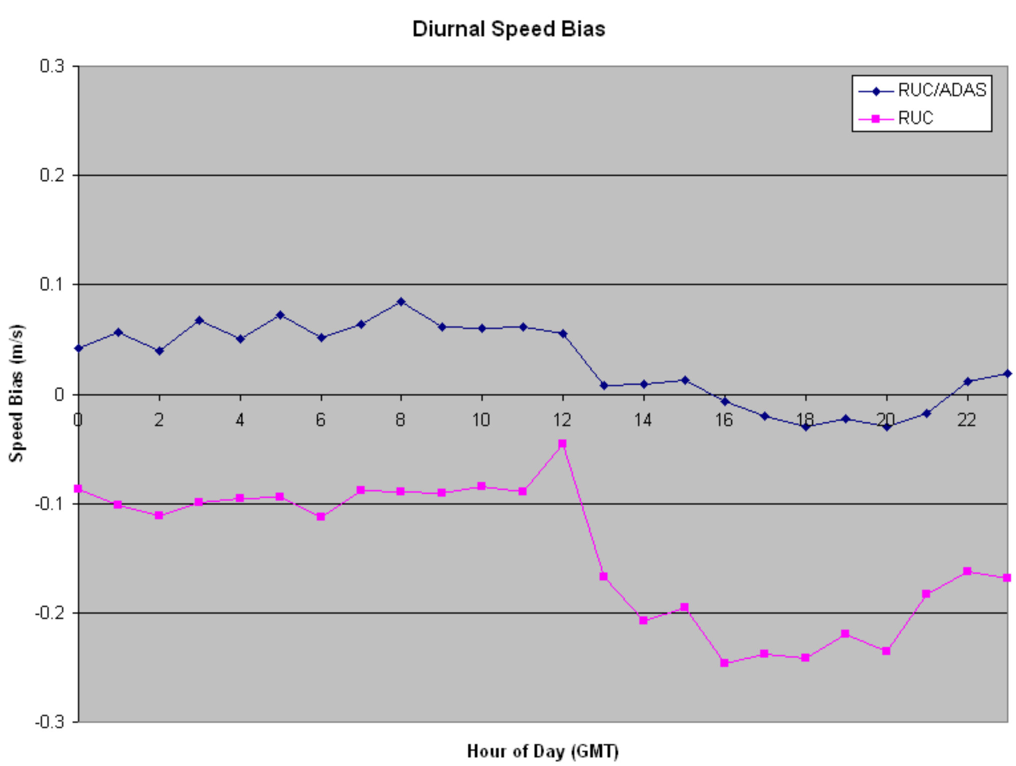

Figure 12. Speed bias as a function of time of day

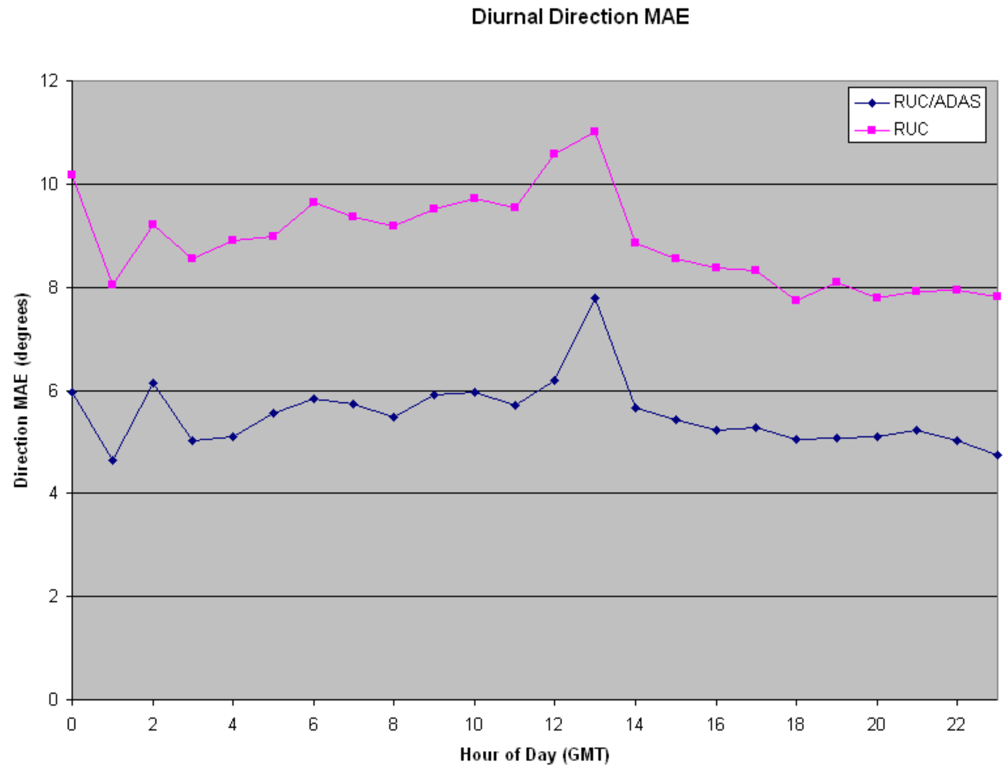

Figure 13. Direction MAE as a function of time of day

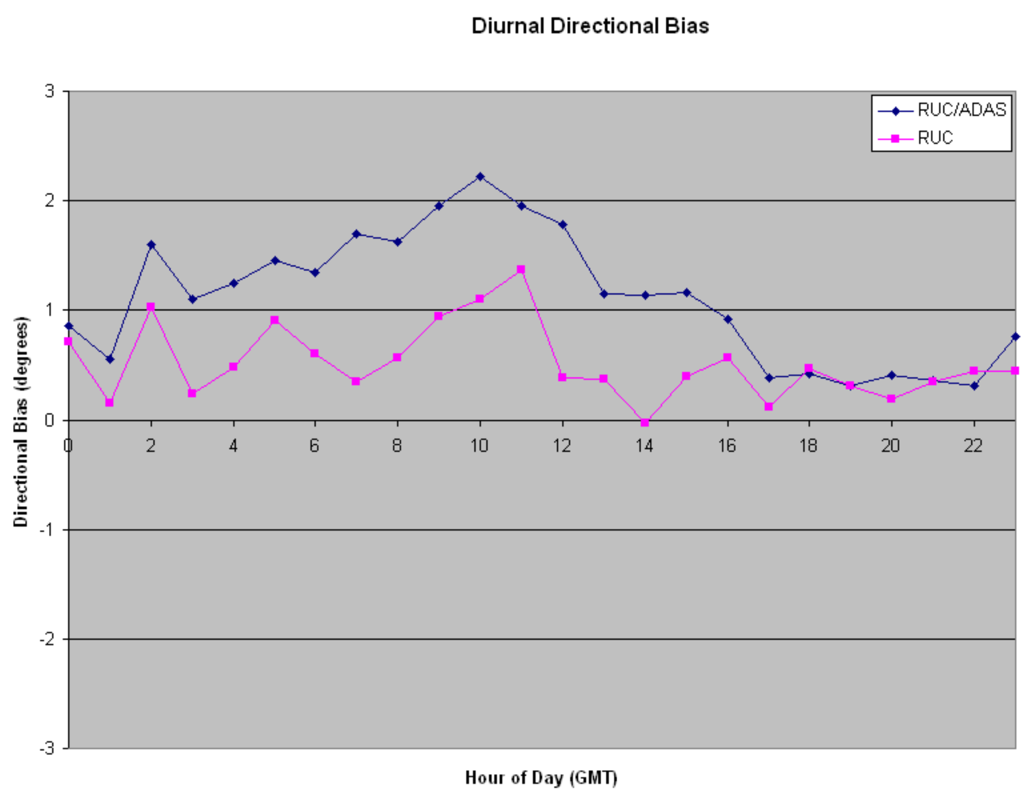

Figure 14. Directional Bias as a function of time of day

Error characteristics were also considered as a function of the time of year. No significant trends emerged, although some subtle effects were evident. Figures 15 shows the speed MAE by month. It is a bit surprising that the RUC MAE values tend to be slightly higher during the warm season months when the speeds are lower. This trend is corrected in the ADAS process. In figure 16 we see that the RUC directional MAE tends to be higher in the summer months, which agrees with the earlier observation that the direction errors are greater for low wind cases. In figure 17 we see that the coefficient of determination, R^2, drops slightly for RUC, and to a lesser extent for RUC/ADAS, in the summer months, again related to the greater incidence of low wind speeds during that time of year.

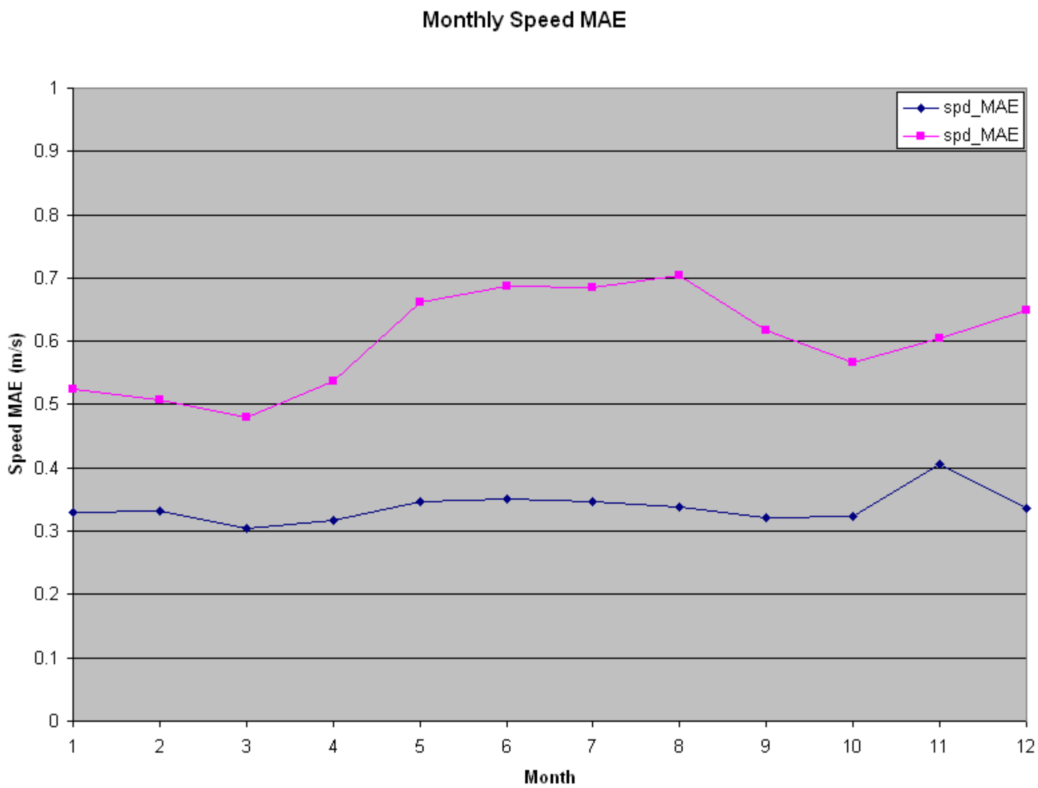

Figure 15. Speed MAE as a function of month of the year.

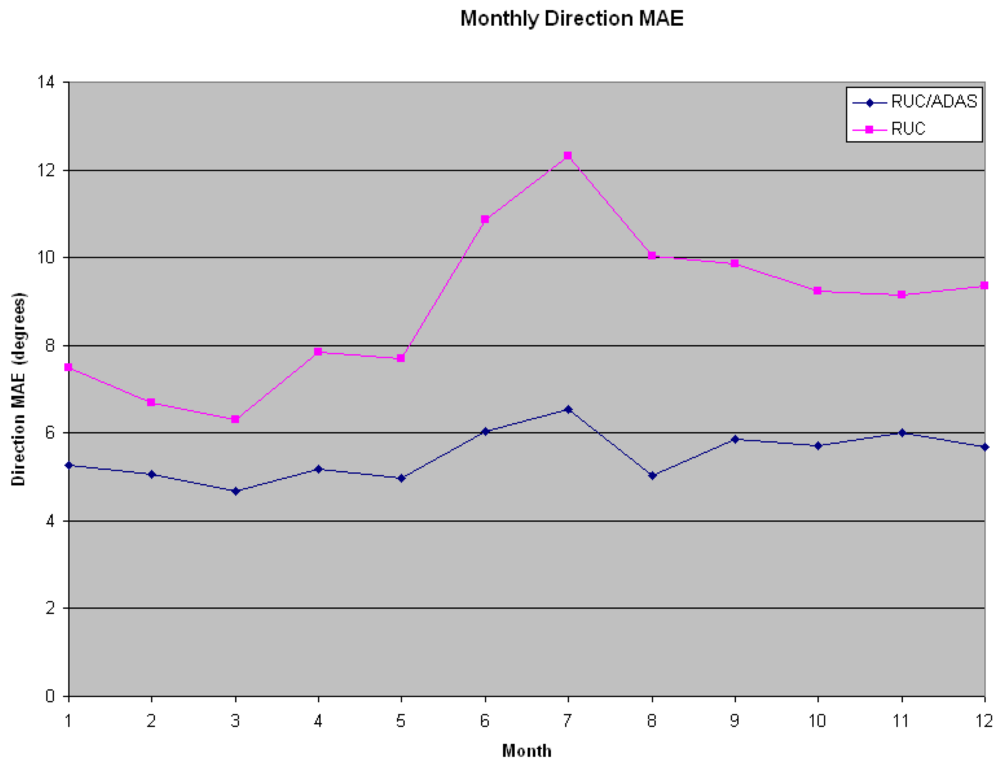

Figure 16. Directional MAE as a function of month of year.

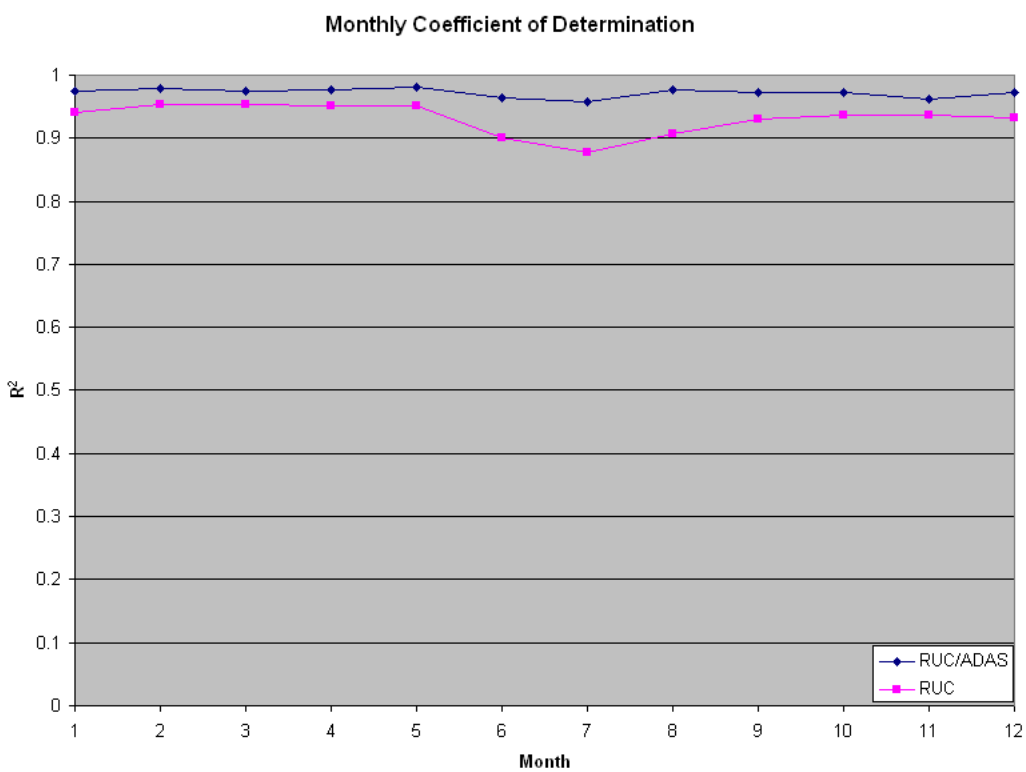

Figure 17. Coefficient of Determination as a function of month of the year

Concluding Remarks:
The hourly RUC analyses have been identified as a useful, and potentially highly accurate source of first-guess winds for the CALMET modeling process. In this paper we have taken a look at the surface wind error characteristics of the RUC data over a domain in the Northern Plains. The RUC grid cell size for the current study was 40 km, while the model has been running in 20 km mode for the last couple of years. The principle advantage of this dataset is that they are analyses that are created as part of a NOAA continuous assimilation process. Being analyses, they would be expected to have lower error than prognostic (forecast) model runs, at least in areas where the RUC system has sufficient grid resolution to represent the relent flow features. This was certainly confirmed, with overall speed MAE values less than 0.6 m/s and vector errors of less than 1 m/s, this compares to typical prognostic modeling speed errors of 2-3 m/s. It should be pointed out that the observations used to check against the RUC data "should" have been seen by the RUC system and used in the data analysis, and it appears that most of them were. To that extent, this is a measure of the ability of the RUC system come up with a reasonable assimilation of the observations.

The RUC data was utilized as the first guess source for the ADAS mesoscale assimilation system, which then re-introduced the surface observations onto a finer 10 km grid. The intent was an enhancement of the RUC data to include additional observations that may have been missing in the real-time RUC process, and by employing a finer grid, make it easier to accommodate small-scale variability of the wind. Typical wind speed and direction errors for this system were 40% lower than for the raw RUC data. It should be stressed that the data used for evaluation was also used in the preparation of the fields, so this amounts to primarily a examination of the ability of the assimilation process to produce accurate analyses, which is very different than a forecast accuracy experiment. But this difference, analysis versus forecast, is the core rationale for using this data. Undoubtedly some of the improvement was due to the finer grid size and some due to the availability of some observations that were not available to the real-time RUC system. It is not possible to break down how much of the improvement was attributable to what cause. This was not a comparison of the relative merits of the RUC versus the ADAS assimilation system, but a first-cut test of the error characteristics of the dataset prepared for the State of North Dakota.

In practice, the RUC/ADAS fields are introduced into CALMET as first-guess fields, and the normal CALMET process of blending in surface and upper air observations is performed. It might be argued that the ADAS step of re-introducing the observations was an "extra step", since they would be brought into the CALMET process anyway. This was done for two reasons: First, the RUC data had to be processed onto an MM5 grid system anyway to accommodate the CALMET MM5.DAT input format, and this was done through the ADAS system, so at that point it was relatively easy to perform the assimilation. Second, based on past experience, and confidence in the assimilation algorithms, we believed that the ADAS system would do an excellent job of re-introducing the data, which I believe was borne out in these results. That being said, a skilled CALMET practitioner would very likely be able to get similar results using the raw RUC (processed onto an MM5 grid structure and written into MM5.DAT format) for the first guess fields and re-introducing the data just in CALMET. A test of that assertion would be a logical follow-on to the current study.

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About the Author

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Dr. Moon has extensive experience in data analysis and numerical simulation of physical systems and is a recognized meteorologist and weather modeler. He directed the development of the Environmental WorkBench interactive 3D visualization application for environmental data, developing the set of user oriented functional requirements, and managing implementation in close collaboration with the software engineers. He has worked on a number of monitoring and simulation projects including the implementation of a real-time meteorological monitoring system for the Hanford Meteorological Station DOE site. He managed the development of a real-time wind field and toxic dispersion modeling system for the city of Cincinnati. He designed and provided scientific oversight for the deployment of sophisticated weather modeling system for the Israeli Air Force. He was the prime architect of the WindLogics wind characteristics analysis system that has been successfully used at a large number of sites across the US and the world. He has played a key role in a number of WindLogics project relating to simulation and analysis of wind patterns. He is a member of the American Meteorological Society.

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